

Research Article

A New Method for Identifying the Life Parameters via Radar

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It has been proved that the vital signs can be detected via radar. To better identify the life parameters such as respiration and heartbeat, a novel method combined with several signal processing techniques is presented. Firstly, to improve the signal-to-noise ratio (SNR) of the life signals, the signal accumulation technique by FFT is used. Then, to restrain the interferences produced by moving objects, a dual filtering algorithm (DFA) which is able to remove the interferences by tracing the interfering spectral peaks is proposed. Finally, the wavelet transform is applied to separate the heartbeat from the respiration signal. The method cannot only help to automatically detect the existence of human beings effectively, but also identifying the parameters like respiration, heartbeat, and body-moving signals significantly. Experimental results demonstrated that the method is very promising in identifying the life parameters via radar.

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1. INTRODUCTION

The life-detection system can be used to search living objects after the earthquake and building collapse, also to monitor patients in clinic without contacting the subjects. In addition, it can be used by law-enforcement services to search criminals hiding behind various covers. The life detection based on radar techniques has been attracting more attention these years. The continuous-wave (CW) radar is widely used to detect the life parameters because of its simple structure and high sensitivity [1–5]. The frequency-modulated continuous-wave (FM-CW) radar is also used [6]. They can detect the life parameters of human noncontact, even behind the barrier such as the brick walls, debris, and clothes. The radar detector radiates electromagnetic waves to human subjects and receives echo waves modulated by the body surface jiggle caused by their physiological activities. The life parameters such as respiration and heartbeat can be extracted according to the frequency or phased variations of the echo waves.

For all the life-detection systems via radar, it is difficult to detect the weak life signals from the strong echo waves of background. There exist two problems ineffectively resolved in common: how to improve the SNR and how to restrain the strong randomness, time variability and sensitivity to the interferences produced by the moving objects further

aggravate the situation, especially for the strong interferences produced by the people walking around the life-detection system, of which the amplitude is much stronger than the body surface jiggle caused by their physiological activities [2]. Hence, it is of great importance to restrain the strong interferences. Using physiological amplifiers with higher precision could improve the SNR, but they are not good to remove the interferences. Some methods for stationary signal processing, including FFT and high-order linear narrowband filtering [7] can also improve the SNR. They may be effective in good circumstances, but may not work in complex situations. Using two antennas, the interferences produced by the moving objects may be partly restrained [8], but the complexity and cost may limit its practical use. The preliminary experimental results showed that the heartbeat signal could be well detected when the human subjects held their breath. However the heartbeat cannot be extracted effectively from the overlapped signals as the breath exists, since the minute chest movement caused by the respiration is stronger than the chest inching caused by the heartbeat, therefore it is difficult to separate the latter from the overlapped signals.

To effectively resolve the problems described above, a new method was proposed, including improving the SNR of the life signals, restraining the interferences produced by moving objects, and separating the heartbeat from respiration signal. To improve the SNR, the signal accumulation

technique by FFT is used, which does not need the a priori knowledge of signal and the period alignment. To restrain the interferences produced by moving objects, a dual filtering algorithm (DFA) is proposed, including two filters and one algorithm by tracing the interference spectral peaks. To separate the heartbeat from respiration signal, the wavelet transform with symmlet mother wavelet is applied. Experimental results demonstrated that the method integrating with the three signal processing techniques above is very promising in identifying the life parameters via radar.

2. METHODS

2.1. Description of the system

The block scheme of the life-detection system and the real system proposed are shown in Figure 1. The electromagnetic wave is generated by the oscillator via a directional coupler. Then it is radiated by the antenna via a circulator. The oscillator operates at 10.525 GHz, and the transmission power is 30 mW. Hence GaAs Gunn diode oscillator is chosen to meet the demands of low noise and low cost, which also can provide linear continuous waves. The system works with only one antenna and the circulator isolates the transmission from the reception. The gain of the antenna is 17 dB, and the beam width is 9° in both the horizontal and vertical directions. Another signal from the directional coupler acts as a local oscillatory signal for the receiver. The echo signal is received by the same antenna and then passes through the circulator to get into the mixer where it is mixed with the local oscillatory signal. The output signal of the mixer contains both the respiration and heartbeat signals with serious noises. It is sent to a preprocessor, where the 50 Hz interference is removed by a band-stop filter, and digitized by A/D converter. Finally, the signals are processed with the proposed techniques and displayed on the monitor.

The signal processing techniques are illustrated in Figure 2. Firstly, the signals are accumulated by FFT to improve the SNR. Then the dual filtering algorithm (DFA) is applied to restrain the interferences produced by the moving objects. Finally, the heartbeat and respiration signals are separated by using the wavelet transform. In the following sections, the signal processing techniques will be discussed in detail.

2.2. Improving SNR by signal accumulation in frequency domain

For the biomedical signals, the processing method usually used to improve the SNR is the signal accumulation in time domain. It needs to know the a priori knowledge of signal such as period, otherwise the signal accumulation in time domain will be difficult. Considering the advantage that the period alignment of a signal is not needed, the signal accumulation in frequency domain has been widely used. The useful signal spectra will be quickly increased by the signal accumulation in frequency domain, while the noise spectra will be increased slowly since the noise is random and its spectrum is

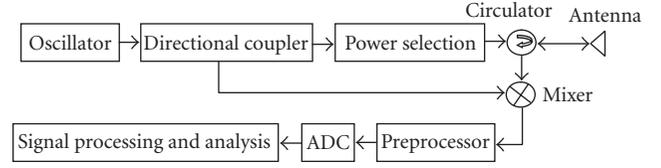


FIGURE 1: The block scheme of the life-detection system.

distributed over a wide frequency range. Therefore, the SNR will be greatly improved through signal accumulation.

Let $x(k)$ be the sequence to be processed, and the length of the sequence is $N = M \times L$, where M is time of accumulation and L is the number of the FFT points. The frequency-domain accumulation can be computed by

$$\begin{aligned}
 X(k) &= \sum_{m=1}^M \sum_{l=0}^{L-1} x_m(l) e^{-j(2\pi/L)lk} \\
 &= \sum_{m=1}^M \sum_{l=0}^{L-1} x_m(l) W_L^{lk}, \quad k = 0, 1, 2, \dots, N-1.
 \end{aligned} \tag{1}$$

2.3. Restraining the interferences using DFA

Generally, the respiration signal is an important life parameter with a narrow frequency bandwidth, which is easily influenced by the interferences produced by the people walking around the life-detection system. So it is difficult to detect the respiration signal from the strong interferences. Using two antennas, the interferences can be partly restrained, but the complexity and cost cannot satisfy the life-detection system [8]. Thus the method named DFA is proposed to restrain the interferences produced by the people walking around the system, which includes two filters and one algorithm. Considering that the respiration signal varies from individual to individual and in abnormal status such as coma or being injured grievously [1], the bandwidth of the first filter is designed wider than that of the normal respiration signal. Then the algorithm is used to identify the spectral peak of the respiration signal and the interference by power-spectrum estimation and cross-correlation coefficient computation after the first filter. Finally the second filter is designed as a notch filter to restrain the spectral peak of the interferences. The DFA is described as follows.

Our study showed that the respiration signal spectral peaks between different individuals have better coherence than that of between the interferences signal spectral peak and the respiration signal spectral peak when the bandwidth is certain. So if the spectral peaks of respiration signal and the interferences can be estimated by using the power-spectrum estimation (PSE) and coherence characteristics of the spectral peaks can be computed, the interference signals and the respiration signals will be identified after the first filtering.

Spectral estimator may be classified as either nonparametric or parametric. The nonparametric estimators require no assumption about the signal other than wide-sense stationarity. The parametric estimators are more restrictive than

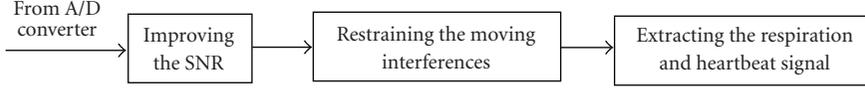


FIGURE 2: The basic flowchart of the signal processing.

the nonparametric ones, but the advantage of the parametric estimator is that when applicable, it yields a more accurate spectral estimation without having to increase the data record length. Because of nonstationarity of the respiration signal and more accurate spectral estimation of the spectral peak, the Yule-Walker autoregression (AR) estimator is used to estimate the power spectrum by computing the autocorrelation function recursively. Let the respiration signal detected by life-detection system in no interferences condition be the reference signal which has better coherence with the practical respiration signal detected by the system than the synthetic oscillatory signal. Assume that the reference respiration signal $x(n)$ has a main spectral peak f_x , and the original signal is $y(n)$ with a spectral peak f_y . The main spectral peak of the reference respiration signal and the original signal can be moved by interpolating in time domain. The formula of the alignment of the spectral peak can be expressed as follows:

$$\begin{aligned} \text{if } f_x \geq f_y, \text{ then } x'(n) &= x\left(\left\lceil n \frac{f_y}{f_x} \right\rceil\right) \quad (n = 0, 1, \dots, N_1 - 1) \\ \text{else } y'(n) &= y\left(\left\lfloor n \frac{f_x}{f_y} \right\rfloor\right) \quad (n = 0, 1, \dots, N_1 - 1), \end{aligned} \quad (2)$$

where N_1 is the total number of the sampling data points, $[\cdot]$ represents the truncation operation, and $x'(n)$ or $y'(n)$ is the interpolating point.

Although the spectral peaks of respiration signal and the interferences could be estimated by using the autoregression power-spectrum estimation (ARPSE), the spectral peaks could not be identified correctly. The study has shown that the respiration signal spectral peaks between different individuals have better coherence than that between the interferences signal spectral peak and the respiration signal spectral peak, so the cross-correlation coefficient ρ of the reference respiration signal spectral peak with each spectral peak is computed by alignment of the peaks of the main frequency spectrum. The ρ indicated the similarity between the spectral peak and the reference respiration signal spectral peak.

The normalized cross-correlation coefficient $\rho(m)$ can be calculated by

$$\rho(m) = \frac{\sum_{n=0}^{N-1} x(n)y(n+m)}{\sqrt{\sum_{n=0}^{N-1} x^2(n) \sum_{n=0}^{N-1} y^2(n)}}, \quad (3)$$

where N is the length of the analyzing window and m ranges from $-(N-1)$ to $(N+1)$. The maximum value ρ_{\max} of $\rho(m)$ indicates the similarity between $x(n)$ and $y(n)$. Comparing

each of ρ_{\max} , if the ρ_{\max} is the least, the possibility of this spectral peak being interferences spectral peak would be the most. Then the spectral peaks with the least ρ_{\max} could be removed by the second dynamic notch filter with the narrow bandwidth. Suppose there are two spectrum peaks f_{y1} and f_{y2} with a common bandwidth ΔB , then one peak should be the spectral peak of respiration signal and the other should be the interference signal. The ρ is computed by (3). Let assume the maximum cross-correlation coefficients of f_{y1} and f_x be $\rho_{\max 1}$ and let that of f_{y2} and f_x be $\rho_{\max 2}$. If $\rho_{\max 1} > \rho_{\max 2}$, then the possibility of f_{y2} being interferences spectral peak would be the most, and vice versa.

After tracing the main spectral peak of the interferences by the algorithm described above, the spectral peak of the interferences and the respiration signal can be identified correctly. So the second dynamic notch filter that traces f_{y2} with bandwidth ΔB is then designed to restrain this spectral peak.

2.4. Separating the heartbeat from respiration signal by wavelet transform

Though the SNR could be improved and the interferences produced by the moving human subjects around the system could be restrained, the principal component of the signal detected by the system is respiration. However, it is necessary to separate the heartbeat signal from the respiration signal when the system is used to monitor the patients in clinical application and so on. Since the minute chest movement is caused by both the respiration and the heartbeat, the possible biological ranges for heartbeat and respiratory frequencies are not well separated and higher-order harmonic components of the lower-frequency respiratory signal can overlap the heartbeat spectrum. Consequently, it is difficult to separate the heartbeat from respiration signal by using linear filters and the power-spectrum estimation [5].

FIR digital filter and adaptive filter had been performed in our experiment, which could not produce the ideal results [1, 2]. The frequency variation in the echo wave modulated by body surface jiggle caused by respiration and heartbeat is very low from 0.03 Hz to 3.3 Hz [1]. Because of the overlapped spectrum of the respiratory and the heartbeat signals, the signal processing methods used are expected to be very sensitive to the frequency variation with higher resolution in time domain. According to the requests of the signal processing described above, the wavelet transform may be used to separate the heartbeat from the respiration signal [9].

The wavelet transform (WT) is a time-scale representation technique with a function of mother wavelet. WT can localize the information of the signal in limited number of the wavelet coefficients according to the discrete wavelet

transform given below:

$$C_{j,k} = \sum_{n \in \mathbb{Z}} x(n)g_{j,k}(n), \quad (4)$$

where $C_{j,k}$ are the wavelet coefficients, and $g_{j,k}(n) = 2^{-j/2}g(2^{-j}n - k)$ is the scaling function.

In the lower frequency band, the wavelet transform has lower time resolution, but higher frequency resolution, and vice versa. This characteristic makes it easier to separate the heartbeat signal from the respiration by wavelet transform. With multiscale decomposition of wavelet, the high-frequency noise and the low-frequency respiration signal could be removed, and the heartbeat signal can be extracted. On basis of the frequency ranges of the heartbeat and the respiration signal computed by Sections 2.2 and 2.3, the algorithm of discrete wavelet transform is outlined below:

- (1) apply wavelet transform to the signal with symmlet mother wavelet;
- (2) eliminate high-frequency and low-frequency noises by setting the corresponding wavelet coefficients to zero;
- (3) threshold the coefficients depending on the breath signal variance and the number of samples of the data;
- (4) perform inverse wavelet transformation to obtain the heartbeat signal.

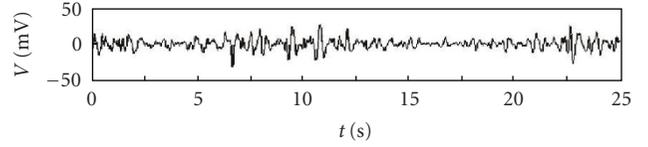
3. EXPERIMENTS AND ANALYSIS

There are 15 healthy volunteers who participated in the experiments including 8 males and 7 females. Their ages ranged from 18 to 50 years old, height from 160 to 178 cm, and weight from 48 to 70 kg. The distance between the antenna and the human subject ranges from 2 m to 8 m. All the experiments described below are in terms of that the subjects' consent was obtained by signing the informed consent form according to the Declaration of Helsinki (BMJ 1991; 302: 1194) and that the Ethical Committee of our university in which the work was performed has approved it. Each of the volunteers is sampled for 20 times under the same experimental condition and there are 4 kinds of conditions. So our total experimental sample size is 1200.

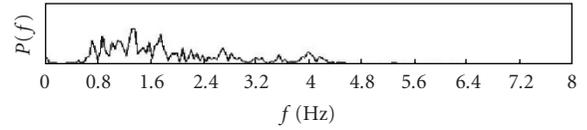
3.1. Improvement of the SNR using signal accumulation

In practice, the noise produced from the radar waves reflected by the wall and ruins is very strong and leads to a low SNR of the weak life parameters, which produces very strong influence. The experiment in this part was proposed to improve the SNR of the life parameters.

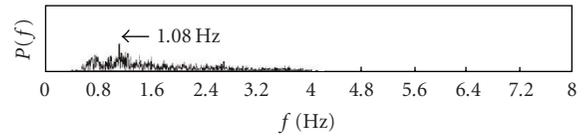
The experiments show that the SNR of the life parameters can be improved. One of the volunteers was a healthy man of 25 years old, 171 cm in height, and 65.5 kg in weight. He sat 2 m away from the antenna and breathed calmly. His pulse rate was around 67 beats per minute. Considering the normal heart rate of the human ranges from 60 to 100 beats per minute, the signal was sampled at 40 Hz for 25 seconds. The representative result is shown in Figure 3. Figure 3(a) shows the time-domain signal detected



(a) The heartbeat signal.



(b) The results based on FFT.



(c) The results based on signal accumulation.

FIGURE 3: The results using the signal accumulation by FFT.

by system. Figure 3(b) shows the frequency spectrum by FFT of 1024 points. Figure 3(c) shows the results of the signal accumulation by FFT with 8192 points. It is clearly seen that the frequency at 1.08 Hz is strengthened and the SNR is improved from Figure 3(c). Note that 1.08 Hz is in good accordance with 67 beats per minute pulse rate of the subject.

3.2. Interferences suppression by DFA

In practice, the radar waves reflected by the wall and ruins are very strong and lead to a complicated electromagnetic environment around the life-detection system. People walking around the system also produce very strong influence to the detection. The experiment in this part was proposed to restrain the interference mentioned above.

One of the volunteers was a healthy man of 25 years old, 171 cm height, and 65.5 kg weight. He sat 8 m away from the antenna and breathed calmly, this distance is maximal where we can detect the heartbeat and respiration signal. His respiration signal was detected in no interferences condition as the reference respiration signal $x(n)$. The signal was sampled at 40 Hz for 25 seconds. To simulate most of the interference sources produced by moving objects ranging from 2 m to 8 m behind the antenna [1, 2], another volunteer was behind the antenna 5 m away and walked around the system with the velocity less than 2 m/s in the distance from -3 to $+3$ m. All of the 15 volunteers sitting 8 m away from the antenna were detected, respectively, by the system under the same condition. Their respiration signals were recorded as $y_m(n)$ and m ranged from 1 to 15. One of the representative experiments is described below. The subject was 22 years old, 172 cm height and, 62 kg weight. His respiration signal was recorded as the $y(n)$ in interferences condition. The walking man moved at the velocity of 0.5 m/s in the distance ranging from -3 to

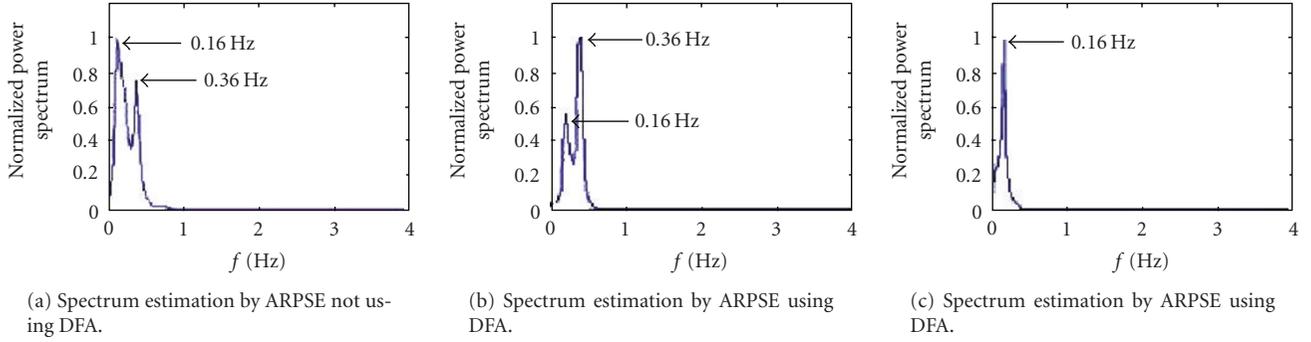
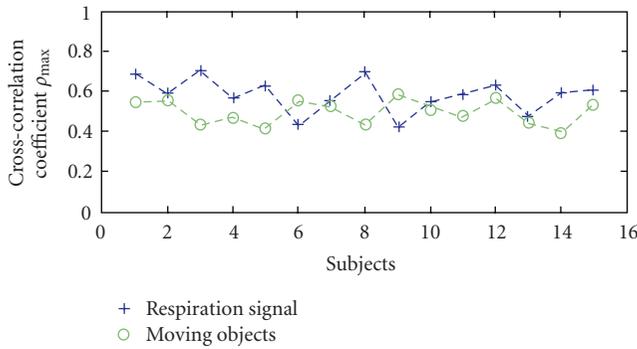


FIGURE 4: The signals processed by DFA.

FIGURE 5: The distribution of the normalized cross-correlation coefficient ρ_{\max} .

+3 m. The spectral peaks of $x(n)$ and $y(n)$ were estimated by ARPSE after the first filtering. All the spectral peaks with unitary power-spectrum density (PSD) bigger than the threshold 0.5 were analyzed. The signal $y(n)$ has two spectral peaks at 0.16 Hz and 0.36 Hz, as shown in Figure 4(a), in which the interference spectral peak cannot be distinguished clearly.

It is suitable to select the bandwidth ΔB as 0.1 Hz according to the results estimated by ARPSE. The maximal cross-correlation coefficient $\rho_{\max 1}$ of $x(n)$ and the spectral peak at 0.36 Hz is 0.6246. The spectral peak processed by DFA is shown in Figure 4(b). The maximal cross-correlation coefficient $\rho_{\max 2}$ of $x(n)$ and the spectral peak at 0.16 Hz is 0.4174. The spectral peak processed by DFA is shown in Figure 4(c). The f_1 at 0.16 Hz is regarded as the interference spectral peak because $\rho_{\max 1} > \rho_{\max 2}$, and is restrained by the digital notch filter with bandwidth 0.1 Hz. After the second filtering, the remaining spectrum with peak at 0.36 Hz is regarded as that of the respiration signal, which is in good accordance with the subject's respiration rate of 20 per minute.

The $y_m(n)$ of each subject has two spectral peaks, one is the spectral peak of respiration signal and the other is the spectral peak of interference signal. The normalized maximal cross-correlation coefficients ρ_{\max} of 15 subjects are shown in Figure 5. Compared with the actual respiration

rate, the symbol “+” indicates the maximal cross-correlation coefficient $\rho_{\max+}$ of $x(n)$ and the spectral peak of the respiration signal. The symbol “o” indicates the maximal cross-correlation coefficient $\rho_{\max o}$ of $x(n)$ and the spectral peak of the interference caused by moving objects. According to DFA, the subject 6 is a man of 50 years old and the subject 9 is a woman of 25 years old, the respiration signals are regarded as interference signals mistakenly because $\rho_{\max+} < \rho_{\max o}$. The reason is possibly that the interference signals have good similarity to the reference respiration signal, while the respiration signal patterns of the subjects have poor similarity to the reference respiration signal. The detection correctness ratio is 86.67%.

3.3. Extraction of the heartbeat signal by symmlets wavelet

The symmlets wavelet has been found to be optimal in terms of its general characteristics, such as compact support, orthogonality and symmetry. The preliminary experimental results also showed that the symmlet mother wavelet of order 8 to be the optimal compared to other wavelet basis functions such as Harr and Daubechies wavelet in our application.

The one-dimensional wavelet decomposition based on 8-order symmlets wavelet is decomposed for 10 scales. In order to compare it with the ECG signal of the same subject simultaneously, the two-channel physiological recorder LMS-2B is used to collect the ECG signal. The frequency bandwidth of recorded signals is from 0.05 Hz to 100 Hz, sampled at 1000 Hz.

If the bandwidth of original signal detected by the system estimated by ARPSE under the same condition as in Section 2.3 is $[0, \Omega]$, it can be divided into the lower half-band from 0 to $\Omega/2$ and the higher half-band from $\Omega/2$ to Ω for every wavelet decomposition scales. In this part, the signal is decomposed into different frequency components by symmlets wavelet in different scales. We use soft thresholding method to eliminate noise from the wavelet coefficients by replacing the coefficients that are in the range of $[-\delta, \delta]$ with zero, while the others are shrunk in absolute value. The

threshold δ proposed by Donoho [10] is

$$\delta = \sqrt{2 \log(N) \bar{\sigma}^2}, \quad (5)$$

where $\bar{\sigma}^2$ is the estimation of the respiration and noise variance and N is the data length.

The higher half-band WDC of the first, fourth, fifth, and sixth scales lower than the given threshold is quantified as higher frequency noise, while the lower half-band WDC of scales left lower than the given threshold was quantified as lower frequency noise. Total 25000 points of signal data are analyzed. The results are shown in Figure 6. Figure 6(a) is the original signal, where the respiration signal is a dominant component and the heartbeat signal is difficult to identify. Figure 6(b) is the profile of the respiration signal in time domain extracted by the digital filter proposed, while Figure 6(c) shows the profile of the heartbeat signal extracted by WT. Figure 6(d) is the ECG signal collected by the physiological recorder. Comparing Figure 6(c) with Figure 6(d), we can see that the rhythm of the heartbeat signal waveform detected by the life-detection system and that of ECG signal detected by the physiological recorder are quite identical. It suggests that heartbeat signal could be extracted effectively from the respiration signal detected by the life-detection system, even with strong background noise.

4. DISCUSSION AND CONCLUSION

In remote life-detection system, one of the key problems is to improve the SNR. The signal accumulation with FFT enhances SNR obviously without the envelope alignment and the period alignment. The number of FFT points L defines the resolving power in frequency. Increasing L would improve frequency resolution and increase the effectiveness of the signal accumulation.

The other key problem is the suppression of interferences produced by moving objects, especially for the interferences from objects walking around the life-detection system. In this study, the DFA algorithm is used to track the spectra of interferences signal dynamically and restrain the interferences without adding any assistant hardware. At the same time, our study shows that the notching bandwidth ΔB of the second filter has effect on the performance of the DFA algorithm. If the bandwidth ΔB is too wide, the useful information would be also restrained. To avoid it, the threshold value for the spectral peaks should be adjusted according to the practical situation. The limitation of the DFA algorithm is that it can only be used to track two interference spectral peaks and the interferences similar to the standard respiration signal cannot be restrained effectively. If the number of the interference spectral peaks is greater than 3, the complexity will increase greatly and the operational speed will be very slow.

In good conditions, respiration signal could be extracted by linear filters. However, the extraction of the heartbeat signal is very difficult due to the effects of breathing and body surface involuntary inching of subjects. FIR digital filter and adaptive filter had been performed in our experiment, which

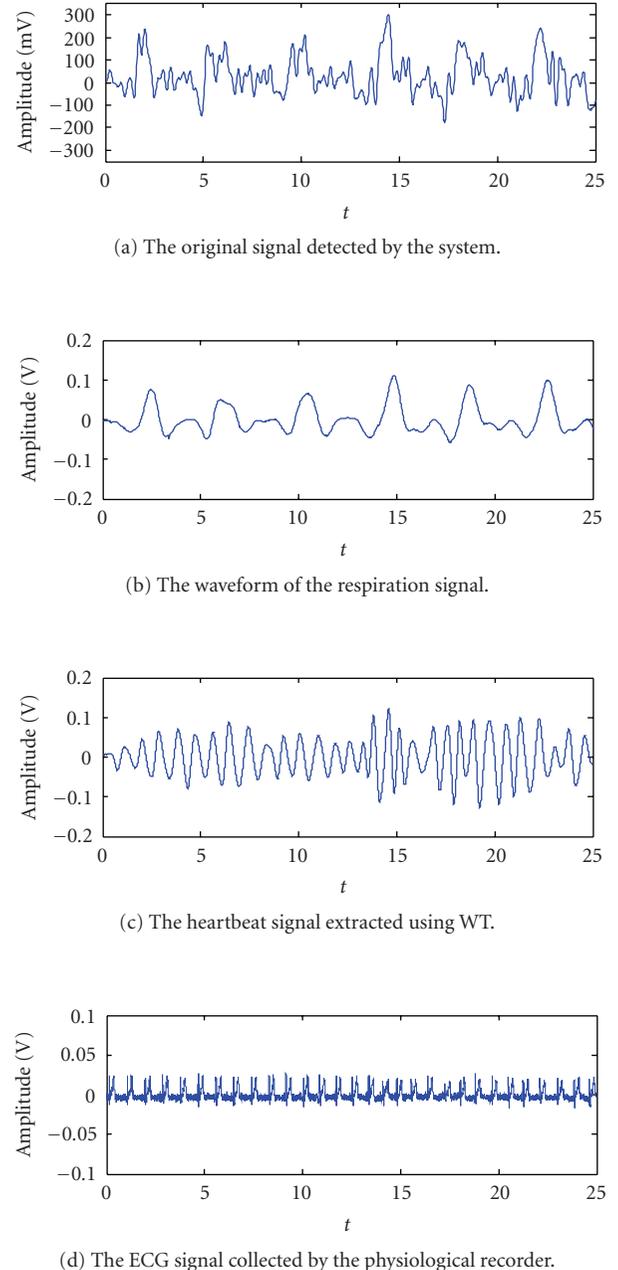


FIGURE 6: The extraction of heartbeat signal by wavelet analysis.

could not produce the ideal results. The wavelet transform technique is very sensitive to the frequency variation with higher resolution in time domain. With one-dimensional wavelet transform technique, the respiration signal and noise could be filtered efficiently, and heartbeat signal can be extracted with obvious frequency characteristics. More decomposition scales would be beneficial to the extraction of the heartbeat signal on the cost of increased computation burden. The optimal number of layers could be determined by experiments.

It is quite difficult to detect the life parameters noncontact. Our study shows that integration of sensitive system based on radar with signal processing techniques is an effective solution. By this way, we can detect some life parameters such as heartbeat, respiration, and body movement without contacting the subject in distance less than 8 m. The possible shortcoming of this method is that interferences similar to the respiration signal cannot be restrained effectively. A sophisticated signal processing scheme with the nonlinear joint phase space may further improve the system performance.

5. SAFETY

The electromagnetic radiation from the life-detection system poses no safety threat. The use of continuous wave radar and relatively short operating ranges allows for very low power levels. The power density level for human exposure can be computed according to the following formula:

$$S(\text{mW}/\text{cm}^2) = \frac{\bar{p} \cdot G}{40\pi \cdot r^2}, \quad (6)$$

where $\bar{p}(W)$ is the average radiating power, $G(\text{dB})$ is the gain of the antenna, $r(\text{m})$ is the distance between the antenna and the human subject.

In our life-detection system, the radiating power is 30 mW and the gain of the antenna is 17 dB. If the minimum distance between the human subject and the antenna is 10 cm, the maximum S is $0.406 \text{ mW}/\text{cm}^2$, which is great lower than the accepted safe power density level for human exposure that is $10 \text{ mW}/\text{cm}^2$ at frequencies from 10 to 300 GHz [11]. In practice the distance between the human subject and the antenna will be further; the power density would be lower.

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